Averting Behavior and Urban Air Pollution

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ABSTRACT. *Unique panel data are used to explain defensive responses to air pollution using determinants predicted by an averting behavior model. Empirical results indicate that persons who experience smog-related symptoms spend significantly less time outdoors as ozone concentrations exceed the national standard. Many people also report making other behavioral changes to avoid smoggy conditions and the propensity to do so appears to increase with schooling or if health symptoms are experienced. Results provide evidence that people adjust daily activities to defend against acute health effects of air pollution, though mitigation appears less closely linked to chronic health impairments.* (JEL Q25)

I. INTRODUCTION

Designing effective public policy to deal with human health hazards requires understanding how behavior responds to changes in risk. If people adjust behavior to offset changes in risk, then: (1) actual health outcomes of a risk change would be overestimated by technological or dose-response models that ignore behavioral adjustments, and (2) changes in time allocations and expenditures on risk-reducing goods may provide useful information about costs and benefits of policy changes (Bartik 1988). Individual averting action also may be a component of socially efficient externality policy (Shibata and Winrich 1983), and some risk communication efforts aim to promote mitigation.

Unfortunately, empirical evidence bearing on connections between risk and behavior is limited and controversial. In consumer product and traffic safety studies such as Viscusi (1984), Evans and Graham (1991), and Keeler (1994), actual behavior is not measured; instead, inferences about behavior are drawn from statistical studies of accident records.[1] Collectively, these studies suggest that a relationship of virtually any strength is possible between risk and behavior, ranging from the technologists' prediction of no effect to Viscusi's (1984) lulling effect in which behavior might more than offset a change in risk. A similar situation prevails among environmental health studies. Although it is sometimes suggested that people take defensive action when pollution increases (Krupnick, Harrington, and Ostro 1990), there have been relatively few attempts to link behavior to measured concentrations of pollution (see Akerman, Johnson, and Bergman 1991; Dickie and Gerking 1991; Doyle et al. 1991; and Smith, Desvousges, and Payne 1995). Related work focusing on actions taken or costs incurred to avoid contaminated water supplies (Harrington, Krupnick, and Spofford 1989; Abdalla 1990; Laughland, Musser, Shortle, and Musser 1996) has provided insights about how behavior responds to environmental hazards, but no clear picture of the connection between behavior and changes in health risk has emerged to assist in formulating public policy.

This paper analyzes unique panel data obtained from a survey of Los Angeles area residents to explain defensive responses to air pollution, especially ozone, using a behavioral model. Panel data are useful here because they allow estimates to control for individual heterogeneity, a potential source of bias in cross-sectional microdata studies.

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[1] An exception is the study of cigarette lighter safety by Viscusi and Cavallo (1994).

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Also, responses to ozone pollution are of interest because: (1) ozone has been linked to acute health impairments in prior epidemiological and medical studies (U.S. EPA 1996); (2) spending less time outdoors effectively reduces exposure (U.S. EPA 1995); and (3) the national ozone standard, currently 12 pphm for maximum one-hour daily concentrations, has been debated intensely since the 1970s and may soon be lowered to 8 pphm (U.S. EPA 1996).

Results indicate that persons who experience smog-related symptoms spend significantly less time outdoors as ozone concentrations exceed the national standard: These individuals are predicted to reduce outdoor time by about 40 minutes on a day when the ozone standard is exceeded, compared to days when the standard is just met. Many people make other behavioral changes to avoid smoggy conditions and the propensity to do so appears to increase with schooling or if health symptoms are experienced. These results support the conclusion that people adjust daily activities to defend against acute health effects of air pollution exposure, but averting decisions appear less closely tied to chronic health impairments.

The remainder of the paper proceeds as follows. Section II outlines an averting behavior model that guides empirical work. Section III describes the data, Section IV presents empirical results, and Section V concludes.

II. MODEL

The model follows closely previous work by Gerking and Stanley (1986) and others. Consequently, discussion focuses only on issues relevant to specification and interpretation of equations estimated in Section IV. An individual's utility function is specified as

$$U = U(X, H, A, \alpha), \quad [1]$$

where X denotes consumption of a composite good and H represents current health status, $U_X > 0$, $U_H \geq 0$, and where health, in turn, is produced according to the household production function

$$H = H(A, \alpha, K, S). \quad [2]$$

In equations [1] and [2], α denotes the concentration of air pollution, with $H_\alpha < 0$, $U_\alpha \leq 0$, and A represents an activity which may affect both health and utility, such as participation in an outdoor leisure activity. Marginal effects of A on H and U may vary in sign. For example, spending more time outdoors may improve current health status if pollution concentrations are low, but may damage it if concentrations are high. For clarity, A is assumed to reduce H at ambient levels of α ($H_A < 0$) so that averting behavior involves *decreasing* A.

Remaining variables in the health production function denote the stock of preexisting health capital (K) and other human capital (S), where $H_K \geq 0$, $H_S \geq 0$. An individual with a chronic disease such as asthma has a lower stock of preexisting health capital, and all else equal has a lower short-term health status. Likewise, persons with less schooling or other human capital may be less efficient producers of H.

The individual maximizes utility subject to the health production function and full-income budget constraint

$$I + \omega T = q_X X + q_A A + q_M M(H) + \omega G(H), \quad [3]$$

where I, ω, and T, respectively, denote nonlabor income, the wage rate, and total time available. Also, $q_j = p_j + \omega t_j$, $j = X, A, M$, denote full, time-inclusive prices of X, A, and medical care M: p_j represents the unit money price and t_j represents time required to consume one unit of good j. The functions $M(H)$ and $G(H)$ take nonnegative values and, respectively, represent medical care consumption and time lost from market and nonmarket activities as a function of current health status, with $M_H < 0$, $G_H < 0$. Thus, lower values of H lead to greater medical expenses and more time lost from work and leisure activities.

First-order conditions for constrained utility maximization imply

$$\frac{U_A + U_H H_A}{\lambda} = q_A + (q_M M_H + \omega G_H) H_A. \quad [4]$$

As shown, the individual equates the sum of direct and indirect effects of A on monetized utility (λ denotes the marginal utility of income), to the net marginal cost of A. Alternatively, the term $U_H H_A/\lambda < 0$ could be moved to the right-hand side of equation [4] and viewed as part of the cost of A. Under standard assumptions, first-order equations can be solved to express optimal choices of X, A, and λ as functions of all exogenous variables; for example,

$$A^* = A(q_X, q_A, q_M, \omega, T, I, K, S, \alpha). \quad [5]$$

This equation guides empirical specification in Section IV. Expected signs of partial derivatives of A^* with respect to key arguments of equation [5] are discussed momentarily.

Several variants of this framework have appeared in the literature, including both one-period (e.g., Gerking and Stanley 1986) and multi-period (Cropper 1981) models where medical care is viewed as an input in the health production function, as well as approaches featuring uncertainty about final health outcomes (e.g., Berger et al. 1987). These models often focus on measuring values for pollution changes and thus typically incorporate more restrictive assumptions than those made here. One important condition often assumed is that averting action defends against all adverse consequences of pollution exposure, but provides no further benefit. In some models, then, α and A do not enter the utility function directly (Gerking and Stanley 1986) and in others, health affects utility only indirectly through the budget constraint (Cropper 1981). The present model allows for the more likely event that air pollution and actions taken to avoid it have direct impacts on well-being in addition to their effects on health (α and A enter the utility function directly). These conditions would seriously complicate application of the model to estimate willingness to pay for air quality improvements.[2]

Additionally, averting decisions may sometimes be discrete choices (Dickie and Gerking 1991). Although data used in Section IV include both discrete and continuous measures of averting behavior, the model presented focuses on the continuous case to simplify discussion of comparative statics and because a discrete choice model leads to an equation like [5] for the probability of choosing a discrete averting action. An appendix available from the authors on request outlines a discrete-choice averting behavior model and more completely exposits the present model.

Comparative static results for equation [5] provide a useful basis for interpreting empirical estimates presented in Section IV. Discussion below highlights intuition behind responses to changes in variables most relevant for empirical work: medical costs (q_M), wages (ω), health and other human capital (K and S), and air pollution (α). An income-compensated increase in q_M increases averting behavior, implying that averting behavior and medical care are substitutes. This occurs because the cost of poor health rises with the full price of obtaining remedial medical care, providing an incentive to increase production of health. Thus, the individual averts by reducing A as q_M rises, given that $H_A < 0$. Because $q_M = p_M + \omega t_M$, money and time prices of medical care

[2] Bartik (1988, 123–26) provides a thorough discussion of assumptions important for estimating benefits in the defensive behavior framework. Apart from the "no unavoidable outcomes/no joint production" assumption, these are: (1) no major adjustment costs of reducing defensive action, (2) the defensive expenditure function is known, and (3) the government can influence pollution levels. The third of these usually is taken for granted, while the second is not a requirement but would be a useful simplification. The first assumption rules out sunk costs and could be violated if averting actions included investments in home air purifying or air conditioning systems. These assumptions are not necessary here because benefits are not estimated.

separately affect A in the same direction as the full price.

A higher wage rate also raises opportunity costs of poor health, but simultaneously boosts full prices of both A and X (as well as full income). Consequently, even the pure substitution effect of ω on A is indeterminate in sign. According to equation [5], empirical analyses of averting behavior should control for differences in wages, but without any expectation of the sign of the coefficient of the wage variable.

Compensated effects on averting behavior of changes in preexisting health capital (K), human capital (S), or air pollution (α) are in general indeterminate, an outcome consistent with models developed by Berger et al. (1987) and others. The indeterminacy arises in part because changes in K, S, or α may exert both a direct effect on health (H_K, H_S, or H_α) and an indirect effect operating through the marginal product of averting action (H_{AK}, H_{AS}, or $H_{A\alpha}$). The situation is further complicated because a change in K, S, or α alters the slopes of the budget curve *and* of indifference curves in the A, X plane. In consequence, the "intuitive" predictions that averting behavior increases when α rises, S rises, or K falls can be defended only in specific situations. Sufficient conditions to obtain these results are: (1) $M(H)$ and $G(H)$ both are convex functions, (2) direct and indirect effects on H take the same sign, and (3) the marginal rate of substitution between A and X declines when α or S rises or when K falls.

To illustrate application of these conditions, consider effects of an income-compensated increase in α shown in Figure 1. Initially, the individual faces the nonlinear budget curve BB, which is drawn to reflect convexity of $M(H)$ and $G(H)$. Amount OD of A is consumed at the tangency of BB and the indifference curve UU (obtained after substituting the health production function into the utility function). If H_α and $H_{A\alpha}$ are both negative, an increase in α unambiguously drives up the net marginal cost of A (see equation [4]), so that the new budget curve is steeper and might look like CC. The assumption that $H_{A\alpha} < 0$ implies that an increase in A magnifies the health damage associated with an increment in α and is consistent with evidence showing greater respiratory effects of ozone pollution for longer exposures to ambient concentrations or for higher activity levels (U.S. EPA 1996). Also, the new budget curve CC is drawn so that the initially chosen bundle of X and A remains affordable. Finally, if the marginal rate of substitution between A and X declines with increases in α, then indifference curves become less steep (like VV) and the individual averts by reducing consumption of A from OD to OE.

Similar results can be presented showing how A responds to changes in K or S and Figure 1 can be used to illustrate these shifts. If the three assumptions discussed above are maintained, an increase in S or a decrease in K boosts the net marginal cost of A, reduces the marginal rate of substitution between A and X, and causes a reduction in the amount of A consumed. On the other hand, if these assumptions are relaxed or if ambient pollution concentrations are low enough that increases in A improve health ($H_A > 0$), then the optimal choice of A may move in either direction. This implies, for example, that the response of A to changing pollution levels is partially dependent on initial ambient concentrations of pollution.

Finally, behavioral responses to pollution also depend on the sensitivity of health to pollution, measured by H_α. Under assumptions sufficient to cause averting behavior to rise with pollution, greater sensitivity (a larger absolute value of H_α, measured empirically as a tendency to experience symptoms in smoggy conditions) magnifies the responsiveness of behavior to pollution changes.

III. DATA

Data consist of repeated observations on 226 Los Angeles area residents during 1985–86. This sample, used in previous research on air pollution and medical care consumption (Dickie and Gerking 1991), was drawn from participants in a prior study of chronic obstructive respiratory disease, and

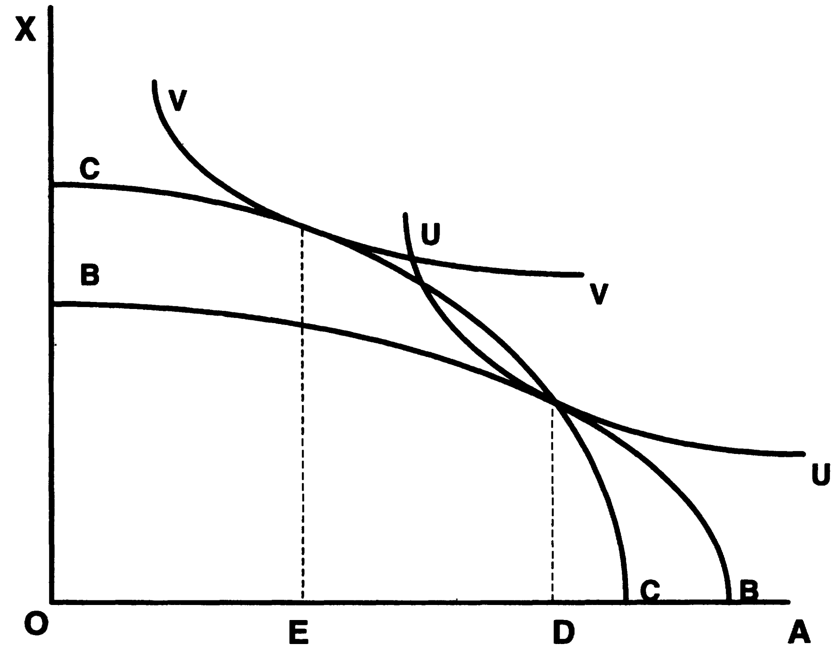

FIGURE 1
INCOME-COMPENSATED EFFECT OF POLLUTION INCREASE ON CHOICE OF A

includes a disproportionate number of individuals with compromised respiratory function. All respondents were either nonsmokers or former smokers who had not smoked for at least two years prior to the initial interview, and all were household heads working at least 1,600 hours annually. About two-thirds of the respondents lived in Glendora (a community with high oxidant air pollution), while the balance lived in Burbank (a community with oxidant pollution more like other urban areas in the U.S., but with comparatively high levels of carbon monoxide).

In the first interview, during July 1985, an extensive baseline questionnaire was administered in the respondent's home. Subsequent (follow-up) interviews were conducted by telephone at later dates over the next 12 months. Respondents were interviewed on different dates in order to increase sample variation of pollution measures, and interviews were scheduled on a mix of weekdays and weekends. The number of contacts per respondent ranged from two to five with an average of just over four, yielding a grand total of 928 observations. The median and modal number of contacts were both five, and all respondents were included in the final survey. Thus, sample attrition would not appear to be a problem and no other data collection difficulties associated with the passage of time are evident. All interviews were: (1) conducted by persons with professional training and experience in survey research and (2) designed specifically to obtain information about averting behavior and health effects of air pollution.[3]

Names, definitions, and summary statistics for variables used in the empirical analysis are presented in Tables 1 and 2. Table 1 lists variables measured only at the time of the baseline interview while Table 2 lists

[3] The same respondents were interviewed again in the autumn of 1986 using a different survey instrument which did not collect data on key variables used in the present study. Thus data from the autumn 1986 survey could not be employed here.

TABLE 1
INDIVIDUAL-SPECIFIC DATA

Variable	Definition	Proportion or Mean (Standard Deviation)[a]
ASTHMA	= 1 if physician diagnosed asthma	.1549
OTHCHRON	= 1 if physician diagnosed other chronic respiratory disease, or report chronic cough or shortness of breath	.5265
HAYFEV	= 1 if physician diagnosed hay fever	.2168
SYMPTOMS	= 1 if experience symptoms when smoggy	.7832
HSGRAD	= 1 if have high school diploma or equivalent	.9336
AGE	= age in 10-year units	4.780 (.7620)
FAMINC	= gross annual household income, in 10,000 dollars (1985)	5.265 (1.883)
WAGE	= hourly wage in dollars	18.79 (12.21)
REGDOC	= 1 if have a regular physician	.8230
MPDOC	= money cost of doctor's visit, net of reimbursement from insurance (dollars)	23.76 (31.94)
TDOC	= commuting plus waiting time to obtain medical care (hours)	.5910 (.2853)
FPDOC	= full price of medical care = MPDOC + WAGE * TDOC	35.04 (33.94)
WRKESGV	= 1 if work in East San Gabriel Valley	.3319
EXPWORK	= 1 if exposed to toxic fumes or dust at work	.4159
BURB	= 1 if live in Burbank (0 if Glendora)	.3319
MALE	= 1 if male	.9248
MARRIED	= 1 if married, living with spouse	.8805
NDEPEN	Number supported with household income	3.403 (1.455)
BLUECOL	= 1 if blue collar occupation	.3097
ACHOME	= 1 if have central air conditioning at home	.3894
APHOME	= 1 if home central air conditioning includes maintained air purifying unit	.08850
NGASCK	= 1 if do not cook with natural gas	.4469
ACTIVITY	= 1 if change planned leisure activities when smoggy	.3894
INDOORS	= 1 if stay indoors more when smoggy	.4027
RUNAC	= 1 if run home air conditioner more when smoggy	.2035
AVERT	= 1 if ACTIVITY, INDOORS, RUNAC, or other change when smoggy	.6549

Note: Data from baseline survey, one observation for each of 226 respondents.
[a] Sample proportions of discrete variables, sample means (and standard deviations in parentheses) of continuous variables.

variables measured during both baseline and follow-up interviews. Variables in Table 1 include measures of preexisting health capital (whether a respondent has physician-diagnosed asthma, hay fever, or other chronic respiratory disease, or chronic coughing or shortness of breath) and sensitivity to air pollution (whether symptoms such as eye irritation, headache, or chest tightness are experienced in smoggy conditions). The variable SYMPTOMS is interpreted as a measure of the pollution-sensitivity of health which would normally be expected to magnify the behavioral response to pollution

TABLE 2
TIME-VARYING DATA

Variable	Definition	Mean (Standard Deviation)
OUTHRS	Hours outdoors, two-day survey period	7.921 (6.160)
NWRKDAY	Number of working days, two-day period	1.095 (8.346)
O_3	Two-day average, peak ozone concentration (parts per hundred million)	9.350 (6.021)
CO	Two-day average, peak carbon monoxide concentration (pphm)	3.429 (2.682)
NO_2	Two-day average, peak nitrogen dioxide concentration (pphm)	8.469 (3.679)
SO_2	Two-day average, peak sulfur dioxide concentration (pphm)	.8317 (.4971)
HTEMP	Two-day average, high temperature (degrees Fahrenheit)	77.46 (12.33)
LHUMID	Two-day average, low humidity (percent)	42.40 (15.90)

Note: Data from baseline and follow-up surveys, two to five observations per respondent for a total of 928 pooled observations.

changes (see Section II). Other variables in Table 1 provide information about: (1) socioeconomic/demographic characteristics (schooling completed, annual household income, hourly wage, and age); (2) air quality in work and home environments (exposure to toxic fumes or dust at work; whether the workplace is located in the highly polluted East San Gabriel Valley; and central air conditioning, air purification, and natural gas used for cooking in the home[4]); and (3) averting behavior (activity changes that may occur during smoggy conditions such as spending more time indoors; increased use of home air conditioning; and limiting, rescheduling, or otherwise changing planned leisure time activities). Staying indoors reduces exposure to ozone, particularly when coupled with use of air conditioning (U.S. EPA 1995).

Measures of averting behavior in Table 1 summarize typical reactions to air quality conditions that respondents perceive as poor. For a given respondent, these variables do not change over the sample period and so cannot be matched to daily measures of ambient pollution. Consequently, the baseline interview collected information on actual activities over the preceding two days, including the number of hours spent outdoors (OUTHRS, see Table 2). Subsequent follow-up surveys also inquired about time spent outdoors during the two days preceding each of these interviews. Thus, the variable OUTHRS is measured repeatedly for each respondent on different days, and can be used to test whether people reduce outdoor time when pollution concentrations are high. Because no corresponding test can be performed for averting behavior variables in Table 1, the two types of measures are analyzed separately using different estimation methods.

In addition to reporting time spent outdoors, respondents indicated the number of days worked during the two-day period (NWRKDAY) on each survey. This variable may indicate flexibility of schedules and may affect daily activities, even assuming the wage equals the marginal value of time. Summary statistics for OUTHRS and

[4] Natural gas ranges emit nitrogen oxides.

NWRKDAY are presented in Table 2 along with information on pollution and weather variables.

Measured concentrations of the six criteria pollutants for which national ambient standards are set were obtained from the monitoring station nearest each respondent's home. Readings for lead and particulates were unavailable for 90 percent of relevant days, however, forcing exclusion of these two pollutants from empirical analysis. Each of the remaining four pollutants—ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2)—was measured at the maximum daily one-hour concentration. Maxima are used because epidemiological evidence suggests that acute health responses are more closely tied to peak than to average concentrations, and day-to-day adjustments in behavior are more likely to be effective in avoiding acute than long-term health effects. Since activity data are aggregated over two-day periods, the air pollution variables used are averages of the peak concentrations on the two days. Daily high temperature and low humidity also are measured as two-day averages.

IV. EMPIRICAL RESULTS

Summary Measures of Individual-Specific Mitigation

As shown in Table 1, almost two-thirds of respondents report changing their behavior in some way on days when air quality is poor. About 40 percent limit or rearrange leisure activities, 40 percent stay indoors, and 20 percent report increased use of home air conditioners. These percentages fall within the range reported in previous studies of defensive behavior. Although the sample proportion that reported some averting action has varied widely in prior research, it appears that the propensity to mitigate is smallest when the purchase of a durable good is involved, and largest during temporary, but extended, periods of water contamination, particularly with public notification of health dangers. Smith, Desvousges, and Payne (1995), who report that radon mitigation often is as costly as the purchase of a durable appliance, find that 15 percent of their sample took action to reduce home radon concentrations. Akerman, Johnson, and Bergman (1991) report a radon mitigation rate that is three times larger, but their sample consisted entirely of individuals obtaining a high radon reading in a previous voluntary test, who presumably were more concerned about radon than the average person. Berger et al. (1987) also examined purchases of durable goods and found that 15 percent of their sample bought air conditioners and 11 percent bought air purifiers at least partly for health reasons. At the other extreme, Harrington, Krupnick, and Spofford (1989) report that 98 percent of their sample engaged in defensive behavior during a giardiasis outbreak, while 76 percent of respondents mitigated in Abdalla's (1990) study of perchloroethylene contamination. Public notification occurred in both of these incidents of water contamination, and very few respondents mitigated by purchasing durable goods such as home filtration systems. Averting behaviors listed in Table 1, which do not involve a current purchase of durable goods but need not follow receipt of special information, lie between these extremes.[5]

Table 3 presents regression analyses to explain variation in overall averting activities. Specification of regressions is based on equation [5] and explanatory variables include measures of health capital and sensitivity to pollution, human capital, and wages, as well as dummy variables controlling for locations of home and work. Effects of medical care costs are examined momentarily, nonlabor income is excluded because the survey did not collect data on it, and the following variables from the theoretical model are excluded because they are assumed to be the same for all respondents: T, p_X, t_X, p_A, and t_A. Finally, as noted in Section III, averting actions listed in Table 1

[5] Laughland et al. (1996) also consider an incident of giardia contamination and report that most respondents took precautionary action. In Abdalla, Roach, and Epp (1992), 44 percent of respondents aware of trichloroethylene contamination mitigated.

TABLE 3
DETERMINANTS OF AVERTING ACTIONS

Explanatory Variable	ACTIVITY	INDOORS	RUNAC
Constant	−3.0587	−1.5233	−2.0045
	(−2.252)	(−1.212)	(−1.326)
SYMPTOMS	1.4435	.83290	.78714
	(3.385)	(2.190)	(1.504)
ASTHMA	.34528	.11805	−.92378
	(.836)	(.287)	(−1.607)
OTHCHRON	.11128	.038020	.39603
	(.358)	(.124)	(1.048)
HAYFEV	−.19270	.96433	1.1038
	(−.523)	(2.688)	(2.726)
HSGRAD	1.5358	.64276	−.14186
	(1.929)	(1.026)	(−.200)
AGE	−.084942	−.089565	−.14127
	(−.432)	(−.460)	(−.597)
WAGE	.003948	−.008048	.005200
	(.327)	(−.602)	(.337)
WRKESGV	.34144	.37191	.72736
	(1.096)	(1.204)	(1.960)
BURB	.31855	.15120	.073415
	(1.009)	(.487)	(.194)
Log-Likelihood	−139.11	−142.82	−104.93
Chi-Square(9)[a]	23.929	19.044	18.518
Number Correct Predictions	132	151	181
Number of Observations	226	226	226

Note: Maximum likelihood logit, estimated coefficients (asymptotic *t*-ratios in parentheses).
[a] Chi-square statistic for testing null hypothesis that all 9 slope coefficients are jointly zero.

(ACTIVITY, INDOORS, and RUNAC) do not change over the sample period and cannot be linked to daily measures of ambient air pollution. Each dependent variable equals one for respondents indicating that they take the corresponding averting action and equals zero otherwise, and estimates are obtained by maximum likelihood logit. Likelihood ratio tests indicate that the decisions to change activities, stay indoors, or use more air conditioning are significantly related to explanatory variables at the 5 percent level or less.

Individuals who report experiencing symptoms in smoggy conditions are more likely to take each of the averting actions, and the coefficient of SYMPTOMS is significant at the 5 percent level in a two-tail test in equations for ACTIVITY and INDOORS. Thus, people who are more sensitive to pollution are more likely to take action to avoid it. Physician-diagnosed hay fever is positively and significantly related to staying indoors and/or running the air conditioner when pollution is high, but presence of ASTHMA or other chronic respiratory impairment does not appear to exert a significant influence on averting decisions. One explanation for these results is that the mitigating behaviors considered defend against symptoms of air pollution exposure, particularly for persons with hay fever, but do not offer any additional health benefit to people with chronic respiratory impairments. Age and locations of home and work appear to have little impact on the propensity to mitigate, while graduation from high school significantly increases the probability of changing activities to avoid pollution.

Further analysis of averting behavior is presented in Table 4, which reports logit regression results for making *any* change in behavior when pollution is high. The dependent variable, AVERT, equals one for respondents reporting that they change activities, stay indoors more, or use more home air conditioning when air quality is poor. The column labelled (1) repeats the specification used in Table 3 regressions, while remaining columns show effects of other explanatory variables. Table 4 results underline the importance of sensitivity to pollution in determining averting behavior. The difference in the estimated probability of averting between those who report symptoms in smoggy conditions and those who do not, when all other explanatory variables are set at sample means in the column (1) regression, is .378. Thus, persons who tend to experience acute health effects of pollution are more than twice as likely as otherwise identical individuals to take action to avoid exposure. This result suggests that people adjust daily activities to mitigate acute health effects of exposure to air pollution. Also, if SYMPTOMS measures the pollution-sensitivity of health (the absolute magnitude of H_α in the model), then this outcome confirms the theoretical prediction that sensitivity to smog affects the behavioral response to poor air quality.[6]

Individuals with more human capital, as measured by graduation from high school, are significantly [at 10 percent in two-tail tests for columns (1)–(3)] more likely to take defensive action. The estimated increase in the probability of mitigation associated with graduation from high school, when all other explanatory variables are set at sample means in column (1), is .255. This outcome is consistent with previous research linking schooling to protective action (Dickie and Gerking 1991) and to more general health-enhancing activities.[7] Results for remaining variables in column (1) are qualitatively similar to estimates presented in Table 3. Effects of chronic health impairments are of particular interest, and while coefficients of ASTHMA, OTHCHRON, and HAYFEV all are positive, none is individually significant at conventional levels, and the set of three coefficients is jointly insignificant at 10 percent.

Regressions reported in columns (2) and (3) of Table 4 show effects of medical costs on mitigation. Both regressions control for whether the individual has a regular doctor and for time and money costs of care. In column (2), the money expense and time required to obtain care are entered separately (MPDOC and TDOC), while the full price of care (FPDOC = MPDOC + WAGE × TDOC) appears in column (3). Coefficients of the full price in column (3) and money price in column (2) are positive, but have *t*-ratios less than unity. The time required to obtain medical care also is positively related to the propensity to mitigate, and its coefficient is significant at the 10 percent level in a two-tail test. Thus, results are not inconsistent with the theoretical prediction that averting behavior substitutes for medical care. Also, previous research with these data shows that lower full prices of medical care or higher ozone levels significantly increase the probability of visiting a doctor (Dickie and Gerking 1991). Taking these two results together provides some, albeit limited, evidence that people weigh benefits of reducing exposure through averting action against expected costs of obtaining remedial medical care.

Column (4) shows effects of household income, demographic characteristics, and variables related to air quality at work and at home. The latter set of variables is included to test whether persons who enjoy better air quality at home are more likely to mitigate, perhaps by staying indoors more in smoggy conditions. As shown, the additional explanatory variables appear largely unrelated to AVERT. The weak effect of income is consistent with a number of studies (e.g., Doyle et al. 1991) but contrasts with some others (Akerman, Johnson, and Bergman 1991; Smith, Desvousges, and Payne 1995). Overall, estimates in Tables 2 and 3 suggest a close link between mitigation and acute health effects of pollution. These results provide only a partial picture of averting behavior, however, because they are not yet tied to measured variations in ambient air quality.

Adjustments in Time Spent Outdoors

As discussed in Section III, respondents reported the total number of hours spent outdoors (OUTHRS) during the two days preceding each interview. These responses can be linked to variations in air quality, and because repeated observations on the same individuals are available, panel data regression procedures can be used to account for unmeasured characteristics of individuals which may affect averting behavior.

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[6] A somewhat similar result was reported by Berger et al. (1987), who found that persons experiencing symptoms (not necessarily related to pollution) were more likely to purchase air conditioners or air purifiers for health reasons. Also, the possibility that SYMPTOMS is an endogenous output of the health production function was tested by estimating a simultaneous equations model for the joint determination of SYMPTOMS and averting behavior. Hausman tests suggest that the variable SYMPTOMS is not an endogenous outcome of averting decisions.

[7] In unreported regressions, additional schooling beyond high school graduation does not appear to increase mitigation.

TABLE 4
DETERMINANTS OF COMPOSITE AVERTING ACTION (AVERT)

Explanatory Variable	(1)	(2)	(3)	(4)
Constant	−.76292	−1.3075	−.76823	−.63145
	(−.568)	(−.905)	(−.557)	(−.379)
SYMPTOMS	1.6195	1.6019	1.5864	1.6466
	(4.470)	(4.331)	(4.344)	(4.376)
ASTHMA	.58695	.64042	.59060	.58870
	(1.189)	(1.288)	(1.206)	(1.187)
OTHCHRON	.35237	.30808	.36602	.36073
	(1.078)	(.923)	(1.115)	(1.065)
HAYFEV	.34843	.29295	.32985	.42088
	(.835)	(.691)	(.781)	(.952)
HSGRAD	1.0609	.99446	1.0380	.89418
	(1.813)	(1.683)	(1.778)	(1.447)
AGE	−.28897	−.26490	−.26785	−.33955
	(−1.323)	(−1.193)	(−1.224)	(−1.376)
WAGE	.004875	.003498	—	—
	(.320)	(.224)		
WRKESGV	.30944	.45505	.35443	.35407
	(.908)	(1.296)	(1.032)	(1.010)
BURB	.20804	.12082	.19461	.24662
	(.617)	(.352)	(.576)	(.685)
REGDOC	—	−.23032	−.22935	—
		(−.548)	(−.554)	
TDOC	—	1.0440	—	—
		(1.740)		
MPDOC	—	.005220	—	—
		(.751)		
FPDOC	—	—	.006445	—
			(.919)	
FAMINC	—	—	—	.039954
				(.413)
BLUECOL	—	—	—	.53393
				(1.371)
EXPWORK	—	—	—	.32519
				(.912)
ACHOME	—	—	—	.14444
				(.396)
APHOME	—	—	—	.21390
				(.364)
NGASCK	—	—	—	.071424
				(.211)
MALE	—	—	—	.48132
				(.631)
MARRIED	—	—	—	.026555
				(.042)
NDEPEN	—	—	—	−.010597
				(−.084)
Summary Statistics:				
Log-Likelihood	−126.58	−124.54	−125.95	−125.11
Chi-Square[a]	38.091	42.174	39.369	41.032
Degrees of Freedom[a]	9	12	10	17
Number Correct Predictions	167	163	166	165
Number of Observations	226	226	226	226

Note: Maximum likelihood logit, estimated coefficients (asymptotic *t*-ratios in parentheses).
[a] Chi-square and degrees of freedom for testing null hypothesis that all slope coefficients are jointly zero.

Regressions to explain variation in outdoor time were computed using both fixed effects and random effects estimators. The fixed effects model treats unmeasured differences between individuals as shifts in the constant term, and is estimated by ordinary least squares after allowing a separate intercept for each person. These intercepts capture effects on OUTHRS of all individual-specific, time-invariant characteristics such as health status and schooling. Thus, coefficients for fixed individual characteristics are not estimated, and only covariates which change over time enter the fixed effects regression: measures of pollution, weather, and the number of days worked. In contrast, the random effects model treats individual differences as components of the error term, is estimated by generalized least squares, and allows identification of coefficients of individual-specific variables. The random effects regression includes as covariates the time-varying regressors used in the fixed effects approach, as well as the individual-specific variables used in Table 3.

Estimates from both the fixed and random effects frameworks confirm the importance of unmeasured individual characteristics in determining time spent outdoors. In the fixed effects regression presented in column (1) of Table 5, the hypothesis of individual homogeneity is rejected at 1 percent using the test statistic $F(225, 695) = 3.959$. The corresponding random effects regression, reported in column (2), also indicates rejection of individual homogeneity at 1 percent based on the test statistic, distributed as chi-square with one degree of freedom under the null, of 222.98. In addition, summary statistics for both regressions indicate that explanatory variables are significantly related to OUTHRS at less than 1 percent.

Although both fixed and random effects regressions underline the importance of individual heterogeneity, the two estimators are interpreted differently. Inferences based on fixed effects estimation are conditional on individual effects observed in the sample, while random effects estimation supports unconditional inferences with respect to the population (Hsiao 1986, 41–43). The random effects approach, then, is more appropriate for testing effects of pollution on outdoor time in the population. Also, the GLS estimator of the random effects model is efficient if explanatory variables are uncorrelated with unmeasured individual effects, but it is inconsistent otherwise. This potential correlation is important to consider, since unobserved individual effects may include preferences for health, outdoor activities, or cleaner air. In contrast, the least-squares-dummy-variable estimator used in the fixed effects framework is consistent even if effects are correlated with regressors, but it is inefficient because it neglects variation between individuals. Results of Hausman (see Hsiao 1986, chap. 2) tests for inconsistency in the GLS estimator are presented in Table 5. In each case, the corresponding p-values exceed .10. This outcome favors the GLS/random effects approach, and consequently only results from this estimator are presented for broader specifications reported in columns (3) and (4).

Considering first the coefficients of individual-specific variables in random effects regressions reported in columns (2) through (4) of Table 5, outdoor time appears lower for persons with hay fever, but higher for those with chronic respiratory ailments other than asthma. Coefficients of ASTHMA, SYMPTOMS, and remaining individual-specific variables are not significant at conventional levels.

Turning to effects of time-varying regressors, results in Table 5 indicate that people spend less time outdoors on working days and on days with cooler temperatures or higher humidity, though the effect of humidity is not statistically significant. Variations in ambient pollution concentrations do not appear to exert a linear effect on outdoor hours: In columns (1) and (2) no individual pollution coefficient is significant at the 10 percent level in a two-tail test, and the set of four coefficients is jointly insignificant. On further analysis, however, this outcome appears to arise from inadequacies of the linear functional form, which constrains pollution to have a constant incremental effect on OUTHRS. As discussed in Section

TABLE 5
DETERMINANTS OF TIME SPENT OUTDOORS (OUTHRS)

Explanatory Variable	Fixed Effects (1)	Random Effects (2)	Random Effects (3)	Random Effects (4)
O_3	043779	.035724	0.18792	0.45180
	(.754)	(.642)	(1.342)	(1.777)
CO	.21120	.23848	0.25482	0.49113
	(1.376)	(1.653)	(1.766)	(1.817)
SO_2	−.53449	−.63129	−0.64798	−1.7891
	(−1.077)	(−1.332)	(−1.375)	(−1.791)
NO_2	−.072521	−.075546	−0.08489	−0.44201
	(−.924)	(−1.027)	(−1.167)	(−3.029)
HTEMP	.094171	.095806	0.05628	0.05698
	(3.630)	(3.839)	(2.090)	(2.099)
LHUMID	−.017358	−.006753	−0.009426	−0.008314
	(−1.208)	(−.497)	(−0.699)	(−0.612)
$O_{3\text{-}8}$[a]	—	—	0.23643	0.13561
	(—)	(—)	(0.886)	(0.246)
$O_{3\text{-}12}$[b]	—	—	−0.61755	−0.70928
	(—)	(—)	(−2.777)	(−1.483)
$O_3 \times$ SYMPTOMS	—	—	—	−0.36005
	(—)	(—)	(—)	(−1.279)
CO $\times$ SYMPTOMS	—	—	—	−0.32749
	(—)	(—)	(—)	(−1.158)
$SO_2 \times$ SYMPTOMS	—	—	—	1.4325
	(—)	(—)	(—)	(1.289)
$NO_2 \times$ SYMPTOMS	—	—	—	0.46785
	(—)	(—)	(—)	(2.876)
$O_{3\text{-}8} \times$ SYMPTOMS	—	—	—	0.17078
	(—)	(—)	(—)	(0.270)
$O_{3\text{-}12} \times$ SYMPTOMS	—	(—)	—	0.10005
	(—)	(—)	(—)	(0.186)
NWRKDAY	−1.7296	−1.5736	−1.5098	−1.4973
	(−7.072)	(−6.978)	(−6.747)	(−6.659)
SYMPTOMS	—	−.044383	0.02100	−1.1907
	(—)	(−.060)	(0.028)	(−0.690)
ASTHMA	—	−.22249	−0.22573	−0.18811
	(—)	(−.259)	(−0.262)	(−0.222)

II, spending time outdoors may contribute positively to short-term health status and to utility, unless air quality is poor. Accordingly, people may not reduce time outdoors until pollution levels are quite high, and the OUTHRS regression was respecified to test for this pattern of behavior.

Column (3) of Table 5 allows for nonlinear effects of pollution using a regression that is piecewise-linear in ozone. The kinks or "knots" in the function occur at concentrations of 8 pphm (the pre-1979 national standard for total oxidants) and 12 pphm (the current national standard for one-hour ozone concentrations). Coefficients of the variables $O_{3\text{-}8}$ and $O_{3\text{-}12}$ measure *changes* in the regression slope occurring at the knots, while the coefficient of O_3 now measures the slope at concentrations below 8 pphm. At higher ozone levels, the regression slope equals the sum of the coefficient of O_3 plus: (a) the coefficient of $O_{3\text{-}8}$ for concentrations between 8 and 12 pphm, or (b) the coefficients of both $O_{3\text{-}8}$ and $O_{3\text{-}12}$, for concentrations exceeding 12 pphm. In this way the estimated effect of an increment in ozone may vary with the initial concentration.[8]

[8] Approximately 46 percent of the total observations on O_3 lie below 8 pphm; 18 percent lie between 8 and 12 pphm, and the remaining 36 percent exceed 12 pphm.

TABLE 5
(CONTINUED)

Explanatory Variable	Fixed Effects (1)	Random Effects (2)	Random Effects (3)	Random Effects (4)
OTHCHRON	—	1.7656	1.6622	1.6945
	(—)	(2.765)	(2.596)	(2.684)
HAYFEV	—	−1.9422	−1.8344	−1.8568
	(—)	(−2.547)	(−2.400)	(−2.463)
HSGRAD	—	−1.8255	−1.9156	−1.8474
	(—)	(−1.460)	(−1.529)	(−1.492)
AGE	—	−.18185	−0.19032	−0.21857
	(—)	(−.443)	(−0.463)	(−0.537)
WAGE	—	.0022619	0.001878	−0.00028
	(—)	(.089)	(0.074)	(−0.011)
WRKESGV	—	−.84804	−0.77380	−0.81077
	(—)	(−1.295)	(−1.179)	(−1.254)
BURB	—	.38387	0.24985	0.31561
	(—)	(.456)	(0.297)	(0.378)
Constant	—	4.7744	6.7955	7.7620
	(—)	(1.465)	(2.062)	(2.189)
Heterogeneity:[c]				
$F(225,695)$	3.959	—	—	—
$\chi^2(1)$	—	222.98	230.19	233.27
Hausman: χ^2	—	11.72	10.99	20.31
(Degrees of Freedom)	—	(7)	(9)	(15)
Regression Slopes:				
F	17.047	—	—	—
χ^2	—	128.50	147.40	160.75
(Degrees of Freedom)	(7,695)	(16)	(18)	(24)

Note: Estimated coefficients (asymptotic *t*-ratios in parentheses).
[a] The variable $O_{3\text{-}8} = O_3 - 8$ if $O_3 > 8$, zero otherwise. Measures excess of observed ozone concentration over proposed standard of 8 pphm.
[b] The variable $O_{3\text{-}12} = O_3 - 12$ if $O_3 > 12$, zero otherwise. Measures excess of observed ozone concentration over current national standard of 12 pphm.
[c] Tests null hypothesis of no individual-specific variation net of effects of explanatory variables.

Estimated slope changes occurring at ozone concentrations of 8 and 12 pphm should not be taken literally as indicating discrete changes in behavior, because the choice of these locations for the knots is arbitrary. Other specifications of nonlinear effects of ozone yield similar results, however, suggesting that estimates presented illustrate qualitatively the way behavior changes as ozone concentrations rise.[9] Also, current and proposed standards are natural points of policy interest, and the current standard of 12 pphm may serve as a focal point for individual awareness or public dissemination of information. Only ozone is specified in piecewise-linear form because it is the only pollutant with peak concentrations exceeding relevant one-hour standards and in unreported regressions, coefficients of nonlinear terms involving other pollu-

[9] In unreported regressions, knots also were specified at ozone concentrations of 10 pphm (the California state one-hour standard) and 20 pphm (the level defined as the Stage 1 air pollution episode in the California Air Pollution Emergency Episode Plan, see California Air Resources Board 1986). Separately, pollutants were entered both linearly and in squared form. Though quantitative results differ across specifications, each regression indicates a significant reduction in outdoor time at high ozone levels. For example, the regression including a squared ozone variable indicates that outdoor time falls with ozone increments above 13.5 pphm.

tants, as well as temperature and humidity, were not statistically significant.[10]

In any event, coefficients of the six pollutant regressors in the column (3) regression are jointly significant at less than 1 percent, suggesting that the absence of a significant pollution effect in columns (1) and (2) can be attributed to the linear functional form. The large negative coefficient of $O_{3\text{-}12}$ indicates that people spend less time outdoors as ozone concentrations exceed the current national standard. Coefficients of SO_2 and NO_2 are negative but insignificant, while CO has an unexpected positive association with OUTHRS.

The final regression reported in column (4) of Table 5 allows effects of pollution on outdoor time to depend on whether symptoms are experienced in smoggy conditions. Coefficients of interaction terms measuring products of pollutants and the dummy variable SYMPTOMS, which was a key determinant of individual-specific averting action, reflect differences in effects of pollution between those who report smog-related symptoms and those who do not. The null hypothesis that these six coefficients are jointly zero is rejected ($p = .04$), indicating that the response to pollution differs according to whether or not a person experiences symptoms.[11] This result provides further evidence for the theoretical presumption (see the end of Section II) that the pollution-sensitivity of health affects the responsiveness of behavior to changes in environmental quality.

Further perspective on the relationship between pollution and outdoor time can be obtained from Table 6, which shows estimated responses of OUTHRS to one pphm increases in concentrations of each pollutant. Results are presented for the full sample based on the column (3) regression of Table 5, and separately by pollution sensitivity based on column (4). Marginal effects are calculated as derivatives of predicted OUTHRS with respect to pollutants. For the full sample, for example, marginal effects of CO, SO_2, or NO_2 equal coefficients of these variables, while the marginal effect of ozone depends on the initial concentration and is computed by summing relevant coefficients. Similar computations are performed separately by SYMPTOMS based on the column (4) regression.[12]

Estimated marginal effects for the full sample indicate that people spend significantly less time outdoors as ozone concentrations rise above the current national standard. Because of the arbitrary placement of the knots in the regression, this result need not imply that people immediately reduce outdoor time as the standard is breached. Rather, estimates suggest that people spend less time outdoors when ozone concentrations reach high levels. Results presented in the two right-hand columns of Table 6 indicate that curtailment of outdoor activities as ozone levels rise occurs primarily among persons who suffer from smog-related symptoms. These individuals are predicted to spend 0.211 of an hour (about 12 minutes) less time outdoors over a two-day period for each one pphm increase in the ozone concentration above 12 pphm. For comparison, a reduction in high temperature of about 4 degrees Fahrenheit would reduce predicted outdoor time by the same amount. Taking Burbank and Glendora to-

[10] All pollutants are initially measured as daily peaks of one-hour concentrations, yet only ozone exceeds relevant one-hour standards. The national CO standard for one-hour concentrations of 35 ppm was not exceeded in California during 1985–86 (see California Air Resources Board 1986). National standards are not set on a one-hour basis for SO_2 or NO_2, but the California one-hour concentration standard for each is 25 pphm, which exceeds any observed values in the data. Regressions were estimated in which each pollutant, temperature, and humidity were entered linearly and as squares, but no squared terms except ozone were significant.

[11] Additional regressions were estimated allowing the effect of pollution on outdoor time to vary with schooling, chronic health impairments, or full prices of medical care; however no significant differences were found in these cases.

[12] For example, the marginal effect of ozone on OUTHRS for persons without symptoms, based on column (4) and assuming an initial concentration between 8 and 12 pphm, is $\partial(\text{OUTHRS})/\partial(O_3) = \beta_1 + \beta_2$, where β_1 and β_2 denote coefficients of O_3 and $O_{3\text{-}8}$. For persons with symptoms, the corresponding effect is $\partial(\text{OUTHRS})/\partial(O_3) = \beta_1 + \beta_2 + \delta_1 + \delta_2$, where δ_1 and δ_2 denote coefficients of SYMPTOMS $\times$ O_3 and SYMPTOMS $\times$ $O_{3\text{-}8}$.

TABLE 6
REPONSES OF OUTDOOR HOURS TO ONE PPHM CHANGES IN POLLUTANTS

Pollutant	Full Sample[a]	No Smog-Related Symptoms[b]	Smog-Related Symptoms[b]
Ozone, Initial Concentration			
Below 8 pphm	0.188	0.452	0.092
	(1.342)	(1.777)	(0.581)
8 to 12 pphm	0.424	0.587	0.398
	(2.396)	(1.630)	(2.000)
Above 12 pphm	−0.193	−0.122	−0.211
	(−2.339)	(−0.642)	(−2.310)
Carbon Monoxide	0.255	0.491	0.164
	(1.766)	(1.817)	(1.054)
Sulfur Dioxide	−0.648	−1.789	−0.357
	(−1.375)	(−1.791)	(−0.677)
Nitrogen Dioxide	−0.085	−0.442	0.026
	(−1.167)	(−3.029)	(0.316)

Note: Estimated effects (and asymptotic *t*-ratios).
[a] Based on column (3) of Table 5.
[b] Based on column (4) of Table 5.

gether, the average daily maximum ozone concentration on days when the standard was exceeded was about 18 pphm in 1985 (California Air Resources Board 1986). Thus, estimates presented imply that individuals who experience smog-related symptoms spend about 40 minutes less time outdoors per day, on the typical high ozone day, compared to a day when the standard is just met. In any event, it appears that persons likely to be the most sensitive to ozone do the most to avoid exposure to high concentrations.

Estimated responses of OUTHRS to changes in other pollutants highlight further differences between individuals depending on sensitivity to smog. The unexpected positive, significant effect of CO occurs only among those not reporting symptoms. On the other hand, these individuals appear to reduce outdoor time significantly as SO_2 or NO_2 concentrations rise, while those reporting symptoms do not.

Although only a few studies have linked mitigation to measured concentrations of environmental contaminants, estimates presented here are broadly consistent with results obtained in earlier work. Akerman, Johnson, and Bergman (1991), Doyle et al. (1991) and Smith, Desvousges, and Payne (1995) show that the probability of mitigation increases with measured radon concentrations in the home, while Dickie and Gerking (1991) treat medical care as an averting good and find that higher ozone concentrations increase doctor visits. Krupnick, Harrington, and Ostro (1990) do not measure mitigation directly, but present results suggesting that persons experiencing acute symptoms take defensive action to reduce ozone exposure on subsequent days. Estimates reported in the present paper point to a similar, though not identical, conclusion: persons most likely to experience symptoms, whether or not experiencing the symptoms concurrently, try to prevent acute health effects from occurring as ozone levels rise.

V. CONCLUSIONS

This paper has used unique panel data on Los Angeles area residents to document defensive responses to urban air pollution and to explain these responses based on determinants predicted by an averting behavior model. The majority of respondents report changing their behavior in smoggy conditions, and individuals who experience smog-related symptoms are far more likely to avert than those who do not. In contrast, presence of chronic respiratory impairments does not appear to be a significant determinant of the types of defensive behavior considered here. The estimated impact of schooling on averting behavior confirms previous research showing a positive relationship between schooling and health-enhancing activities, and results are weakly consistent with the theoretical prediction that averting behavior increases with medical costs. Estimates presented also indicate that people spend less time outdoors as air quality deteriorates, a result broadly consistent with the few earlier studies linking mitigation to measured quantities of pollution. Persons who report symptoms in smoggy conditions, while adjusting outdoor time less than others in response to changes in sulfur dioxide and nitrogen dioxide, curtail outdoor activities more as ozone concentrations rise. Overall, results suggest that people adjust daily activities to mitigate acute health effects of air pollution.

These results help to clarify the link between air quality and avoidance behavior, but the extent of defensive action may be understated here, owing to two research limitations. First, the analysis links daily activities to daily pollution concentrations; data on potential long-term adjustments were not collected. A person who made a permanent decision to reduce exposure by taking recreation indoors or in early morning hours, for example, might not alter his/her behavior when pollution levels are high. Second, the sample is not representative of the U.S. population: it includes disproportionate numbers of married men who work, nonsmokers, and persons with chronic impairments. Although sex, marital status, and presence of chronic conditions were not significant determinants of averting behavior in the equations estimated, some caution is warranted in drawing inferences about the general population. Perhaps more importantly, the sample consists of individuals who have chosen to live in rather polluted areas. These people may be relatively unconcerned about health effects of air pollution and so less prone to mitigate than persons living elsewhere. Further research is warranted to investigate a broader set of averting actions in a more representative sample, and perhaps to link mitigation decisions with the choice of residential location.

In any event, the conclusion that people attempt to avert acute health effects of air pollution has potentially important implications for estimation of health effects and benefits. If defensive behavior in fact reduces acute impairments, then estimators of health effects or benefits based on dose-response functions which ignore averting behavior may be seriously biased. Future research should assess the effectiveness of averting action and the potential bias by estimating a health production function with outdoor time, and possibly other averting behaviors, as inputs. Earlier work by Krupnick, Harrington, and Ostro (1990) provides some evidence on the impact that controlling for outdoor time has on estimated health effects. In that study, "exposure-adjusted" pollution measures were constructed by adjusting ambient concentrations based on time spent outdoors, appliance use while indoors, and the degree of intrusion of ambient pollution into residences or workplaces. The magnitude and statistical significance of the ozone coefficient are greater when ambient pollution concentrations are replaced by exposure-adjusted measures in a dose-response model of acute health effects. While this adjustment controls for variations in time spent outdoors, it does not eliminate the potential bias because it does not account for the endogenous choice of outdoor time. Addressing this endogeneity and the resulting bias is particularly important because it appears that the largest reductions in outdoor hours occur (1) when ozone levels are highest and (2) among persons most likely to experience ozone-related symptoms.

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